INVITED PAPER

Autonomous Ground Vehicles—Concepts and a Path to the Future

This paper gives an overview of the most current trends in autonomous vehicles, highlighting the concepts common to most successful systems as well as their differences.

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ABSTRACT | Autonomous vehicles promise numerous improvements to vehicular traffic: an increase in both highway capacity and traffic flow because of faster response times, less fuel consumption and pollution thanks to more foresighted driving, and hopefully fewer accidents thanks to collision avoidance systems. In addition, drivers can save time for more useful activities. In order for these vehicles to safely operate in everyday traffic or in harsh off-road environments, a multitude of problems in perception, navigation, and control have to be solved. This paper gives an overview of the most current trends in autonomous vehicles, highlighting the concepts common to most successful systems as well as their differences. It concludes with an outlook into the promising future of autonomous vehicles.

KEYWORDS | Autonomous driving; control; environment perception; light detection and ranging (LIDAR); machine vision; navigation; unmanned ground vehicles (UGVs)

I. INTRODUCTION

Autonomous driving started in the 1980s, when Carnegie Mellon University (CMU, Pittsburgh, PA) presented its Navlab vehicles that operated in structured environments [1], and when the University of the Bundeswehr Munich (UniBw Munich, Neubiberg, Germany) showed early results in high-speed motorway driving [2]. At EUREKA-PROMETHEUS project's final demonstration in 1994, UniBw Munich and Daimler-Benz presented autonomous driving in three-lane French Autoroute traffic with speeds up to 130 km/h, which included tracking both lane markings and other vehicles. The system decided when to change between lanes by itself, although the approval of a human driver was required for safety reasons [3].

Today, some aspects of these early achievements have reached series production in the form of driver assistance systems for cars. Lane detection is used to facilitate lane departure warnings (LDWs) for the driver and to augment the drivers heading control in lane keeping assist systems (LKAS). The detection and tracking of vehicles driving ahead is used in adaptive cruise control systems (ACC) to keep a safe and comfortable distance. More recently, precrash systems emerged that trigger full braking power to lessen damage if a driver reacts too slowly.

Meanwhile, the attention of research in autonomous vehicles has switched its focus from the well-structured environments encountered on highways as studied in the beginning to more unstructured environments, like urban traffic or off-road scenarios. This trend has been boosted by the 2001 National Defense Authorization Act, where the U.S. Congress mandated that "by 2010, one third of the aircraft (...) fleet and (...) by 2015, one third of the operational ground combat vehicles are unmanned." Especially for unmanned ground vehicles (UGVs), the Defense Advanced Research Projects Agency (DARPA) is still powering development at universities and in the industry to reach this goal.

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In this paper, we give an overview of current research activities in the field of autonomous vehicles since the DARPA challenges. We present the key concepts that evolved during recent years all over the world and describe the performance of autonomous vehicles today. The paper ends with an outlook on the future of autonomous vehicles.

II. PLATFORMS AND SENSORS

Three elements are common to all autonomous ground vehicles: sensors to perceive the environment and the own movement, on-board computers, and actuators for vehicle control. Fig. 1 shows the LIDARs, cameras and Global Positioning System (GPS) antennas used on three vehicles of the DARPA Urban Challenge teams.

For environment perception, both image-based sensors like monocular and stereo cameras (monochrome and color), and range sensing devices like RADAR and LIDAR are used. The high-definition Velodyne LIDAR with a 360°, 3-D view and rich point cloud was designed especially for autonomous vehicles and is used in many systems. RADAR sensors are additionally able to determine the object's relative velocity directly. Distance-providing image-based sensors are mostly based on a time-of-flight principle. Another principle called light coding is utilized in the low-priced Microsoft Kinect, now popular for indoor robotics. However, both principles are not yet suited for outdoor use in autonomous vehicles because they provide limited range only.

To estimate the vehicle's motion, measurements from odometry and inertial sensors are incorporated, supported mainly by global position measurements from GPS.

Typical sensor setups need to be calibrated: intrinsic parameters like the camera lens' focal length or the orientation of laser diodes must be determined. Sensor fusion additionally requires an extrinsic calibration of all fused sensors, describing the position of each sensor in a common reference frame. Especially for nonrigid frames and platforms, continuously keeping the intrinsic and extrinsic calibration up to date by adjusting it online while the autonomous vehicle operates becomes very important [4]. Sensor fusion is performed in most current systems, especially when complementary sensors like color cameras (good angular resolution, no distance information) and range measuring devices (no color, bad angular resolution, precise distance information) are available. Sensor fusion may then proceed at different levels of abstraction: it is possible to fuse the raw data of the sensors, e.g., to produce a colored point cloud. The next level of fusion is done at the feature level, e.g., tracking a road boundary based on 3-D measurements from LIDAR and image features from vision [5]. The last level of fusion works on the object level, e.g., fusing objects detected by RADAR and LIDAR into a single track estimate [6].

Fig. 1. *In DARPA Urban Challenge 2007, six vehicles finished the race. This image shows "BOSS" (Tartan Racing Team, Carnegie Mellon University, first place), "Junior" (Stanford Racing Team, Stanford University, Stanford, CA, second place), and "Odin" (Team Victor Tango, Virginia Tech, Blacksburg, third place). The sensors on the roofs of these cars are nearly the same: LIDARs, cameras, and GPS antennas.*

All distributed or centralized processing on board the vehicle has to be real-time capable. This is an important prerequisite for vehicle control algorithms and system safety checks.

Actuators are necessary for closing the control loop, e.g., for steering wheel, brake, or throttle control.

For safety reasons, providing redundancy in both sensor setup and data processing is common practice, especially when shifting functionality from a research level to series production level. Still, legal reasons require a human "safety driver" for today's autonomous vehicles to operate in public traffic.

III. PERCEPTION

The ability to perceive the vehicle's local environment is one of the main challenges in the field of autonomous ground vehicles. Environmental conditions like lighting or colors are permanently changing, and there are a lot of static as well as dynamic objects in the scene to be taken into account. The best perceptional results are typically achieved by capitalizing on the strengths of the different sensors mentioned in Section II. In the following, we give examples of important perception tasks in the field of autonomous vehicles and their realizations.

A. Vehicle State Estimation and Ego-Motion Compensation

As a prerequisite for the perception and control modules, a good estimation of the vehicle's motion is necessary. Especially when the vehicle is moving fast or on nonflat terrain, relevant rotation along the longitudinal and lateral axes occurs. Working with measurements which are not taken at one unique timestamp, it becomes important to compensate for the vehicle's ego-motion in all measurements [7]. A reliable position estimation is also essential for trajectory control [8].

For a good estimation of the motion, all measurements regarding the own vehicle are incorporated. Typical measurements are velocity and steering angle from odometry and accelerations, angular rates, and attitude from inertial sensors. Additionally, motion information from visual odometry [9] can be incorporated. Considering the actual length of the suspension struts allows to derive sensor height and the angle to the ground plane. If global position measurements like GPS are available, they can be used to calculate a georeferenced position estimate which is necessary when following global plans. Making use of a motion model for the vehicle, all these measurements are fused using Kalman filter techniques to provide a smooth state estimation. Usually, two different types of position are estimated. 1) A jump-free position estimation which is subject to drift is based on integration of the vehicles's motion only. 2) Another way to estimate the position incorporates global measurements like GPS. This compensates for drift, but frame jumps can occur. Thus, it is less suited to compensate for the vehicle's motion in the sensor data.

B. Static Obstacles

For handling static obstacles in the environment, occupancy grid mapping is commonly used. Data from successive LIDAR point clouds or stereo camera range images is condensed into a regular metric grid. For mapping tasks like this, precise compensation of the vehicle's own movement is important.

Each grid cell stores a probability for the existence of an obstacle at the particular location. Additionally, minimum and maximum height measurements are often recorded to be able to estimate, e.g., the slope of the terrain. Determining a cell's terrain type [10] and color [11] has also been addressed. The size of such maps is restricted to a local area around the autonomous vehicle, and the size limits its maximum velocity. These grids usually do not exceed a size of 200 m $\times$ 200 m, with quadratic cell's edge length varying from 0.1 to 0.5 m. This size and resolution is enough to support most safe driving decisions. Still, if generating a map of the environment is an explicit goal, larger maps can be built the same way. Mapping then has to cope with the large amount of storage space necessary.

Special care must be taken of moving objects, which leave a trail of obstacle cells in the grid [6]. If these objects are known from tracking, their estimated position and motion can be fed back into the grid for clearing the obstacle trails. Alternatively, a visibility analysis can be used to detect those cells as being free again [12].

When moving in a complex environment it is important to not only classify certain static objects, but also to deduce their meaning, e.g., by analyzing visual features of traffic lights and signs.

C. Traffic Participants and Other Moving Obstacles

The knowledge of 3-D position and motion of objects in the scene is essential for a safe motion of the autonomous vehicle in the environment. The motion of different object classes is best described by different motion models. For example, Ackermann-steered vehicles like cars move on clothoid segments, while pedestrians can move in all directions. Their motion is also characterized by different maximum velocities and accelerations, and the behavior of an object may change over time. It is thus desirable to estimate an object's motion by a mixture of different motion models, where the one that currently best explains the observations contributes most to the object's state estimate. State estimation is typically done with some instance of recursive Bayesian filters (BFs), where the most prominent one is the extended Kalman filter (EKF).

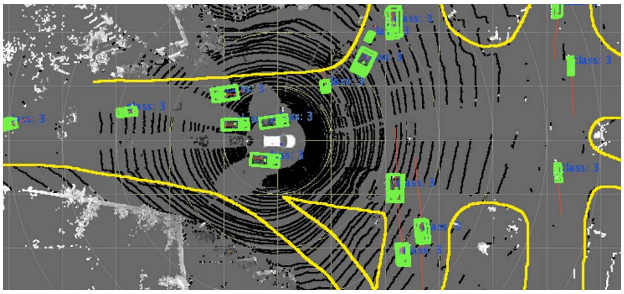
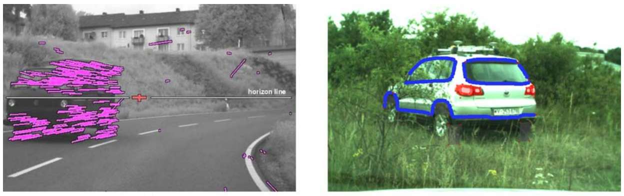


Fig. 2. ***Results of UniBw's LIDAR-based object tracking: black dots represent LIDAR measurements in the ground plane, and brighter dots lie above. Tracked vehicles are drawn as green boxes with arrows pointing into the direction of movement. An approximation of the crossing's geometry (yellow) was added for clarification.***

The Velodyne LIDAR is ideally suited for detecting and tracking objects participating in urban traffic. Fig. 2 shows results of UniBw's tracking system. The basic tracking proceeds by first removing all ground points and performing a 3-D clustering of the remaining points. Object hypotheses derived from the 3-D point clusters are then associated to existing tracks to update the state estimates. Depending on the success of data association, new tracks are added or spurious ones are removed. Mature tracks are finally classified into passenger cars, trucks, bikes, and pedestrians by having a look on the appearance and history of motion behavior.

Several methods exist to detect moving objects in the image plane. One possibility is to segment the image according to the optical flow, grouping pixels that show similar movements [13] [see Fig. 3(a)]. Another one is to use a detector pretrained to find a certain class of object in images. This also allows the detection of static objects. However, one main issue with tracking objects based on monocular camera images still is to initialize and constantly estimate the 3-D position of the object from its detection in the 2-D image plane. Thus, the range information provided by additional range measuring devices, such as stereo camera, RADAR, or LIDAR, is often used for this purpose.

For some highly structured scenarios and with certain simplifying assumptions, the distance to other objects can



(a) (b)

Fig. 3. ***Visual object tracking. (a) Detection using optical flow vectors (magenta) [13]. (b) Monocular model-based 3-D vehicle tracking in unstructured environment dealing with partial occlusions [5]. The blue and red image paintings show the projection of the current 3-D position estimate of the geometric vehicle model onto the image plane.***

also be inferred from a single camera image. For example, a vehicle driving ahead typically casts a characteristic shadow onto the ground. Assuming a flat world, this shadow can be used for estimating the distance and size of the vehicle [3]. These assumptions can be dropped when using monocular motion stereo. Exploiting the observability criterion as defined in modern control theory allows many state variables to be estimated recursively from one moving camera, which would not be observable from static monocular cameras. An example of very precise tracking working in more challenging, off-road environments is shown in Fig. 3(b), where a detailed 3-D model of a certain vehicle with edges and color blobs is utilized in a recursive particle filter tracking framework [5].

D. Road Shape Estimation

Detecting static and dynamic obstacles is not sufficient for autonomous driving, although it helps with safety. For driving in a human-made environment, the ability to perceive the road shape is essential.

There has been much work on tracking lanes on marked roads in 2-D images since the 1980s [3]. Actual systems mostly use clothoidal [6] or B-spline models [14] [see Fig. 4(a)] for 3-D lane representation. Both model parameters and the relative position are estimated using BF derivatives. By projecting the 3-D estimate of the model into the image, a very efficient measurement of directed edges of lane markings can be performed, introduced as "4-D approach" [3]. Additional to painted lines, curbs can also be integrated using LIDAR-based measurements [6].

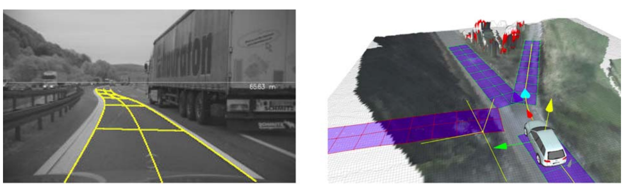
In scenarios with less contrast like on field tracks and forest tracks, the edge-based method alone fails. Using additional image-based measurements like edge direction, color, or texture, and obstacles from an occupancy grid enable navigation in these environments [11] [see Fig. 4(b)].

When navigating on road networks, crossings also have to be detected. The crossing's geometry can be estimated using the same perceptual features as in lane tracking [11], [15]. It is also possible to infer the crossing's geometry from other traffic participants' movements [16].

E. Map-Aided Localization

An imprecise localization of an autonomous vehicle might result in catastrophic behavior. The vehicle could drive on the wrong side of the road, it could believe a goal position to be inside a large obstacle, or it might even expect pedestrians crossing the road to be on the sidewalk. It is well known that GPS signals get weak or corrupted in dense forests [7] or "urban canyons." Modern navigation systems then integrate odometry and inertial sensors to arrive at a diverging solution after a few minutes.

If some sort of map of the environment is known in advance, it can be used to improve localization by associating map features with features found by local sensing and determine the offset. Such approaches are summarized as map-aided localization, and they mostly differ in the kind of map and environment features. All of them again use some sort of BF to recursively estimate the offset from a history of feature associations. In [17], the map is given in terms of a 2-D infrared reflectivity map built from LIDAR data, which is matched against the reflectivities of the current LIDAR point cloud (see Fig. 5). Two approaches use a map describing the road network topology and match it with different kinds of visual features of the road in the current field of view [6], [18]. An interesting approach is that of [19], which uses readily available aerial images, thus avoiding the need to construct a map beforehand.



(a) (b)

Fig. 4. ***Road shape estimation. (a) Lane tracking on a marked highway utilizing a B-spline lane model [14]. (b) Tracking of unpaved roads and crossings in a rural environment [11]. The vehicle is about to turn into the right branch, indicated by the yellow line.***

IV. BEHAVIOR, NAVIGATION, AND CONTROL

Urban and off-road scenarios expose a variety of navigational situations that require an individual treatment, tailored to the given situation. Navigating along an unrehearsed track through a forest under poor GPS conditions might require a different treatment than navigating through open terrain. The same is true for navigating in a parking zone versus driving on highways.

For coordination of behavior in different situations, finite hierarchical state machines are a common tool [6], [12], [20] for the vehicles to decide what to do, but major differences exist in navigation approaches.

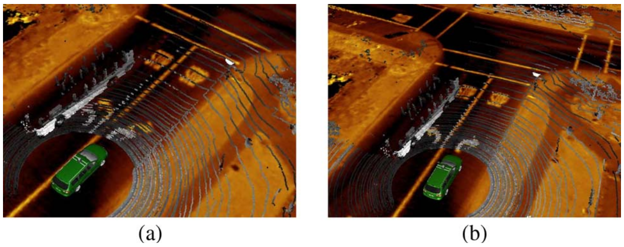


Fig. 5. *Map-aided localization using probabilistic high-resolution infrared remittance ground maps [17]. Incoming laser scans are shown superimposed on a prerecorded map. (a) When using GPS localization only, features from the map (gold) and from the current laser scan (grayscale) show offsets, as can be seen at the road markings. (b) These offsets can be compensated for by map-aided localization.*

A. Global Navigation

In contrast to this demand of flexibility, the concept of "global navigation" still dominates other approaches to autonomous navigation. The vehicle is guided by trajectories [23] derived from planning algorithms operating in global metric maps of the environment [21], as shown in Fig. 6(a).

In global navigation, the map separates the rest of the system from perception: situation assessment, behavior selection, and path planning do not need to know which sensors or algorithms were used to create the map. They just rely on the information contained in it. One of the key tasks is to create the map and maintain its consistency over time. A difficulty is to adjust a once-planned trajectory when the map is updated. Usually, global replanning takes much longer than updating the map with new sensor information. A solution is to locally restrict the search space for replanning by using a global base trajectory as reference [8].

B. Reactive Navigation

Reactive navigation mechanisms can lead to a complete exploration of an environment, when running it long enough. To illustrate this idea, consider a robot that moves within an arbitrary polygon and behaves like a billiard ball. Even when the polygon is very complex the system will eventually explore the complete polygon.

In an autonomous driving scenario, the polygon edges correspond to curbs, other waysides, and obstacles, and the reflection behavior can be replaced, e.g., by an approach like the "tentacles" approach [24]. Fig. 6(c) shows the basic principles of this navigation approach, using a local occupancy grid for obstacle avoidance.

Global navigation does not require any object recognition capabilities, but planning and mapping algorithms. Reactive navigation is just the opposite: a reactive mechanism directly couples navigation to perception. Object recognition is required to decide when the goal has been reached.

C. Guided Navigation

Since global navigation and reactive navigation are antithetic paradigms in terms of planning and perception, it would not be a surprise if there existed a paradigm in between, and indeed it does: we refer to it as guided navigation because it uses structures in the environment whose perception allows the direct estimation of feedback values for control. This approach is in between global and reactive navigation, because it does not use metric planning, yet the motion patterns that result are not random at all.

A good example for guided navigation is the task to follow a road or an off-road track. It is possible to follow a track by perceiving and estimating the curvature and relative state of the track to the vehicle, neither requiring to determine any position nor to plan any trajectory. Instead the trajectory is perceived in terms of the track [3]. Apart

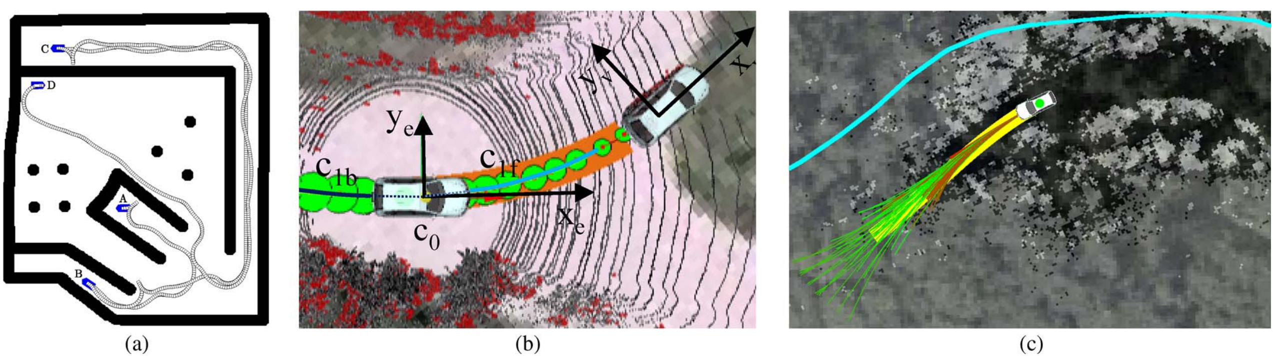


Fig. 6. *Navigation. (a) Global navigation: long-distance navigation results from Urban Challenge finalist Team AnnieWay [21]. Paths were planned from position A to B, B to C, and C to D subsequently. (b) Guided navigation in platooning: a clothoid (orange), fitted to the last estimated leader vehicle positions (green), provides the feedback values for vehicle control. (c) Combined reactive and global off-road navigation with "tentacles." Drivable tentacles, a subset of precalculated feasible driving primitives, colored according to the results of evaluation in an occupancy grid (transparent overlay, brightness indicates obstacle probability), where green tentacles are preferred over red ones. The tentacle selected for motion execution is shown yellow. The large offset between the autonomous vehicle and a GPS target trajectory (cyan) is typical for difficult off-road scenarios [22].*

from track following, there exist numerous more examples where guided navigation is possible: it can be used for platooning [see Fig. 6(b)] [5], for navigation at intersections [11], for approaching a landmark, or for driving through a gate.

Planning is also possible with guided navigation, but not in terms of trajectories but of the structure used for guidance. This way, behaviors like "turn right at the third crossing" can be planned, if the related landmarks can be perceived.

D. Combinations

Depending on the situation one or the other navigation paradigm might be preferable. When trying to park a car into a narrow spot at the other end of the parking field with many obstacles in the way, planning a global trajectory might be the choice. When driving along a path, guided navigation is the natural choice. When no guidance structures exist, perception conditions are bad, or immediate reactions have to be taken, reactive navigation is desirable. Reactive navigation can easily be combined with both other navigation approaches. The tentacles approach to reactive navigation was combined with GPS [see Fig. 6(c)] at competitions like the DARPA Urban Challenge [25] and the European Land Robot Trials (ELROB) from 2007 to 2010 [7], [22]. Similarly, Thrun *et al.* [8] used a reactive approach in combination with a global trajectory.

Global and guided navigations are fundamentally different. However, they can still be combined by temporal chaining or at different levels of navigation. Global navigation is applied at the strategic level, considering larger distances and omitting details. At the finer operational scale, where a high precision is demanded and unexpected events might occur, guided navigation can be used.

V. PERFORMANCE

The DARPA Grand Challenge (GC) was a competition for driverless vehicles, sponsored by the U.S. Department of Defense. The courses of GC 2004 and 2005 led through the Mojave desert and were described by many GPS waypoints. Because in 2004 no vehicle finished, more effort was made to make the competition practicable in 2005. The environment could be assumed to be static, hence the focus was more on perception than on planning. Stanford's car "Stanley" won this race [8], and three other robots finished within the time limit.

A remarkable attempt to show the possibilities of complex robot behavior was the DARPA Urban Challenge (UC) in 2007, where several unmanned cars managed to autonomously drive together with manned cars in urban traffic and to observe the local traffic rules (see Fig. 1). The road network was specified by GPS waypoints in detail. Precise localization on this network and object detection had to be performed by perception, and most teams used global navigation. But the real challenge was to make intelligent decisions when interacting with other cars. Six cars finished successfully; the winner was CMU's "Boss" [6] before Stanford's "Junior" [12].

The success achieved during the DARPA challenges is now continued with Google's driverless car, driven by leading people from Stanford's and CMU's DARPA-Teams. In 2011, they claimed to have driven more than 300 000 km in public traffic [26], but still with occasional manual interventions. They used previously collected data together with actual sensor information from LIDAR and camera to perform a precise localization in a global map. The complete navigation task was done in this global system, of course taking other traffic into account.

German Technical University of Braunschweig, also UC finalist with team CarOLO, presented in 2010 their ongoing project "Stadtpilot." The autonomous car "Leonie" drove within heavy traffic on Braunschweig's inner ring road [20].

The VisLab Intercontinental Autonomous Challenge (VIAC) took three months to autonomously drive a couple of cars from Italy to Shanghai Expo 2010 [27]. The identical cars were equipped with different modes of autonomy, like "lane keeping," "waypoint following," or "leader follower mode," using LIDAR and preferably visual information. The environment consisted of paved and unpaved roads, all with regular traffic, hilly passages, and deserts. Depending on the situation and environment, the leading vehicle used lane keeping capabilities or was driven manually. The following vehicle typically just followed the first one, using vehicle tracking and waypoint following. No global planning was used during this experiment due to a lack of maps for large parts of the course from Italy to China.

ELROB is a yearly trial for autonomous vehicles, targeting university and industry teams. Compared to GC and UC, the environment is by far less structured, with unpaved muddy roads through dense woods, sometimes hilly terrain, and only few moving obstacles. One of the many scenarios is autonomous navigation, with only 10 to 30 waypoints (instead of about 3000 in the GC) describing the coarse way. Since 2007, we have participated with our vehicle Munich Cognitive Autonomous Robot Car, 3rd generation (MuCAR-3) in different scenarios. Our performance increased from year to year [7], [22], [24], dealing with the problems of bad GPS conditions in the dense woods, while GPS offsets of up to 50 m caused trouble to many participants.

VI. PATH TOWARD THE FUTURE

In general, we assume an ongoing technical progress of sensor performance and cost-performance ratio for the future. This covers, among others, improvements of global localization systems by, e.g., using Galileo, more precise inertial sensors, cameras better dealing with bad lighting conditions, miniaturized LIDAR sensors adapted for vehicle integration, active 3-D cameras getting suited to

improvement in gps needed

better sensors

outdoor environments, and of course faster computers to handle this growing amount of data. But sensors are just a prerequisite for better perception, leading to a higher grade of autonomy, and not the key to solve the real problems.

A. Available Today and in the Near Future

Many driver assistance systems which emerged from autonomous vehicles are available for passenger cars today, like the lane keeping assist system (LKAS). In the next years, stop-and-go systems will appear taking over full control of the vehicle. The velocity and the scope at which these systems operate are likely to increase from the traditional "traffic jam on highways" scenarios [28]. More complex scenarios like road construction sites with inconsistent lane markings are another topic of current research [29]. But, for legal reasons, they will still require the driver holding the steering wheel for the next couple of years.

Also in the agricultural sector much effort is invested to achieve a higher level of automation, known as "precision farming." The main objective is to reduce cost as well as pollution: higher machine utilization, lower manpower requirements, and a reduced amount of fertilizer. "Hands-off" driving tractors have been in use for the last decade. They are based either on a guided navigation approach, following structures in the field, or a global navigation approach, precisely following GPS waypoints [30]. Until today the tractors have been manned for supervision because there was no obstacle avoidance. There is development toward unmanned tractors as well, e.g., a team of two vehicles operated by just one operator [31], not yet ready for production. In the agricultural sector, the vehicles operate on a private terrain, possibly fenced, hence unmanned driving seems rather possible from a legal point of view.

In contrast, having a completely autonomous unmanned vehicle in real public traffic is still legally vague. Who is accountable for accidents: the (not-driving) driver, or the car manufacturer? After lobbying from Google's driverless car project, Nevada has passed first laws regarding autonomous vehicles in 2011, at least to facilitate research in this field.

In the next years, autonomous driving in public traffic will still be limited to very structured environments, because even small changes in the environment can destroy the performance of the complete perception system [32].

Redundancy in sensing and processing is important, e.g., by using different principles of sensing (cameras and RADAR/LIDAR), to better cope with environmental effects like direct sunlight. This will help to increase the reliability of autonomous vehicles.

B. Midterm Future

Most current research systems like the Google driverless cars require detailed prerecorded maps to perform their map-aided localization and global navigation task.

In a couple of years, these maps could become more common, like today's vector-based street maps from geo information systems (GISs). An aim could be to have all autonomous vehicles continuously updating these maps, and in addition also sharing them via car-to-car (C2C) and car-to-infrastructure communication (C2I). Issues like how to model the world for building maps, e.g., using landmarks in a topological manner as an alternative to grid-based metric maps, as well as dynamic aspects in maps or limited communication bandwidth have to be dealt with.

For autonomous vehicles in real off-road environments, the problem of correctly classifying obstacles into flexible and thus drivable obstacles like vegetation and real ones like stones as well as better detection of water-based obstacles has to be solved. This includes the intelligence to distinguish a very wet but drivable road from a lake or a flat water-filled pothole from a deep pothole.

A robust system is based not only on the perception itself but also on a kind of self-reflection to be aware of the reliability of sensor and perception modules [33], [34]. Additionally, there is the requirement to develop strategies to safely cope with untrustworthiness of perception in planning.

It is very interesting to observe that even car manufacturers opposed to or at least not pushing autonomous vehicles in the past now investigate such systems, up to autonomous driving tests on public roads [35]. So the field is gaining momentum, and it now seems more likely than just a couple of years ago that we will experience autonomously driving vehicles in everyday traffic within the next 10–15 years.

C. Possible Long-Term Future

Venturing an outlook to the long-term future, much research work is necessary to make more cognitive systems and reach a higher grade of autonomy. Autonomous vehicles will become more sophisticated in a more abstract, human-like way, i.e., relative to other objects: "Follow this road to the red church, turn right and stop at the bakery with a big tree in front of it."

An important step toward this goal is learning, e.g., how other vehicles look like and move, and using this knowledge for perception, navigation, and interaction purposes. The knowledge has to be continuously updated, and some parts can be forgotton, e.g., when uncertainty grows over time. For adapting the vehicle's behavior to the owner's one, e.g., more sporty or comfortable, the human's driving behavior could be observed, but the resulting behavior must always comply to traffic rules. One example is imitation learning, meaning deducing the vehicle's behavior from the observed behavior of other traffic participants or from manually operated runs [36]. However, there will always be unexpected situations never seen and "learned about" before, which the vehicle nevertheless has to cope with.

The difficult interaction between autonomous vehicles and other traffic participants, both robots and humans, will also need more work. For this purpose, the information about the behavior and intentions of other traffic participants has to be gathered.

The terrain today called off-road is mostly just rural, e.g. , small paths through a wooded area or fields. For performing in real off-road terrain, much work has to be done for classification and path planning in full 3-D, e.g., dealing with overhanging obstacles, and very different soil conditions.

All in all, much more work is required until autonomous vehicles can safely and robustly participate in real-world urban traffic as well as in complex off-road scenarios. ■

REFERENCES

[1] C. Thorpe, M. Hebert, T. Kanade, and S. Shafer, "Toward autonomous driving: The CMU Navlab. Part II: System and architecture," *IEEE Expert*, vol. 6, no. 1, pp. 44–52, Aug. 1991.

[2] E. D. Dickmanns and A. Zapp, "Autonomous high speed road vehicle guidance by computer vision," in *Proc. 10th IFAC World Congr.*, 1987, vol. 4, pp. 232–237.

[3] E. D. Dickmanns, *Dynamic Vision for Perception and Control of Motion*. London, U.K.: Springer-Verlag, 2007.

[4] J. Levinson, J. Askeland, J. Becker, J. Dolson, D. Held, S. Kammel, J. Z. Kolter, D. Langer, O. Pink, V. Pratt, M. Sokolsky, G. Stanek, D. Stavens, A. Teichman, M. Werling, and S. Thrun, "Towards fully autonomous driving: Systems and algorithms," in *Proc. IEEE Intell. Veh. Symp.*, 2011, pp. 163–168.

[5] M. Manz, T. Luettel, F. von Hundelshausen, and H.-J. Wuensche, "Monocular model-based 3D vehicle tracking for autonomous vehicles in unstructured environment," in *Proc. IEEE Int. Conf. Robot. Autom.*, 2011, pp. 2465–2471.

[6] C. Urmson, J. Anhalt, D. Bagnell, C. Baker, R. Bittner, M. N. Clark, J. Dolan, D. Duggins, T. Galatali, C. Geyer, M. Gittleman, S. Harbaugh, M. Hebert, T. M. Howard, S. Kolski, A. Kelly, M. Likhachev, M. McNaughton, N. Miller, K. Peterson, B. Pilnick, R. Rajkumar, P. Rybski, B. Salesky, Y.-W. Seo, S. Singh, J. Snider, A. Stentz, W. Whittaker, Z. Wolkowicki, and J. Ziglar, "Autonomous driving in urban environments: Boss and the urban challenge," *J. Field Robot.*, vol. 25, no. 1, pp. 425–466, Jun. 2008.

[7] T. Luettel, M. Himmelsbach, F. von Hundelshausen, M. Manz, A. Mueller, and H.-J. Wuensche, "Autonomous offroad navigation under poor GPS conditions," in *Proc. 3rd Workshop Planning Perception Navigat. Intell. Veh./Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst.*, pp. 56–62, 2009.

[8] S. Thrun, M. Montemerlo, H. Dahlkamp, D. Stavens, A. Aron, J. Diebel, P. Fong, J. Gale, M. Halpenny, G. Hoffmann, K. Lau, C. Oakley, M. Palatucci, V. Pratt, P. Stang, S. Strohband, C. Dupont, L. E. Jendrossek, C. Koelen, C. Markey, C. Rummel, J. van Nieker, E. Jensen, P. Alessandrini, G. Bradski, B. Davies, S. Ettinger, A. Kaehler, A. Nefian, and P. Mahoney, "Stanley: The robot that won the DARPA grand challenge: Research articles," *J. Robot. Syst.*, vol. 23, no. 9, pp. 661–692, 2006.

[9] M. Schweitzer, A. Unterholzner, and H.-J. Wuensche, "Real-time visual odometry for ground moving robots using GPUs," in *Proc. Int. Conf. Comput. Vis. Theory Appl.*, 2010, pp. 20–27.

[10] K. M. Wurm, R. Kümmerle, C. Stachniss, and W. Burgard, "Improving robot navigation in structured outdoor environments by identifying vegetation from laser data," in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst.*, 2009, pp. 1217–1222.

[11] M. Manz, M. Himmelsbach, T. Luettel, and H.-J. Wuensche, "Detection and tracking of road networks in rural terrain by fusing vision and LIDAR," in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst.*, 2011, pp. 4562–4568.

[12] M. Montemerlo, J. Becker, S. Bhat, H. Dahlkamp, D. Dolgov, S. Ettinger, D. Haehnel, T. Hilden, G. Hoffmann, B. Huhnke, D. Johnston, S. Klumpp, D. Langer, A. Levandowski, J. Levinson, J. Marcil, D. Orenstein, J. Paefgen, I. Penny, A. Petrovskaya, M. Pflueger, G. Stanek, D. Stavens, A. Vogt, and S. Thrun, "Junior: The Stanford entry in the urban challenge," *J. Field Robot.*, vol. 25, no. 9, pp. 569–597, 2008.

[13] J. Klappstein, F. Stein, and U. Franke, "Monocular motion detection using spatial constraints in a unified manner," in *Proc. IEEE Intell. Veh. Symp.*, 2006, pp. 261–267.

[14] H. Loose and U. Franke, "B-spline-based road model for 3D lane recognition," in *Proc. IEEE Intell. Transp. Syst. Conf.*, 2010, pp. 91–98.

[15] C. Duchow, "Videobasierte Wahrnehmung markierter Kreuzungen mit lokalem Markierungstest und Bayes'scher Modellierung," Ph.D. dissertation, Karlsruher Institut für Technologie, Karlsruhe, Germany, 2011.

[16] A. Geiger and B. Kitt, "ObjectFlow: A descriptor for classifying traffic motion," in *Proc. IEEE Intell. Veh. Symp.*, 2010, pp. 287–293.

[17] J. Levinson and S. Thrun, "Robust vehicle localization in urban environments using probabilistic maps," in *Proc. IEEE Int. Conf. Robot. Autom.*, 2010, pp. 4372–4378.

[18] I. Miller, M. Campbell, and D. Huttenlocher, "Map-aided localization in sparse global positioning system environments using vision and particle filtering," *J. Field Robot.*, vol. 28, no. 5, pp. 619–643, 2011.

[19] O. Pink, F. Moosmann, and A. Bachmann, "Visual features for vehicle localization and ego-motion estimation," in *Proc. IEEE Intell. Veh. Symp.*, 2009, pp. 254–260.

[20] F. Saust, J. Wille, B. Lichte, and M. Maurer, "Autonomous vehicle guidance on Braunschweig's inner ring road within the stadtpilot project," in *Proc. IEEE Intell. Veh. Symp.*, 2011, pp. 169–174.

[21] J. Ziegler, M. Werling, and J. Schröder, "Navigating car-like robots in unstructured environments using an obstacle sensitive cost function," in *Proc. IEEE Intell. Veh. Symp.*, 2008, pp. 787–791.

[22] M. Himmelsbach, T. Luettel, F. Hecker, F. von Hundelshausen, and H.-J. Wuensche, "Autonomous Off-Road Navigation for MuCAR-3—Improving the tentacles approach: Integral structures for sensing and motion," *Künstliche Intelligenz*, vol. 25, no. 2, pp. 145–149, 2011.

[23] M. Werling, L. Gröll, and G. Bretthauer, "Invariant trajectory tracking with a full-size autonomous road vehicle," *IEEE Trans. Robot.*, vol. 26, no. 4, pp. 758–765, Aug. 2010.

[24] F. von Hundelshausen, M. Himmelsbach, F. Hecker, A. Mueller, and H.-J. Wuensche, "Driving with tentacles: Integral structures for sensing and motion," *J. Field Robot.*, vol. 25, no. 9, pp. 640–673, 2008.

[25] S. Kammel, J. Ziegler, B. Pitzer, M. Werling, T. Gindele, D. Jagzent, J. Schröder, M. Thuy, M. Goebl, F. von Hundelshausen, O. Pink, C. Frese, and C. Stiller, "Team AnnieWAY's autonomous system for the DARPA Urban Challenge 2007," *J. Field Robot.*, vol. 25, no. 9, pp. 615–639, 2008.

[26] S. Thrun and C. Urmson, "Self-driving cars," *IEEE/RSJ Int. Conf. Intell. Robots Syst.*, San Francisco, CA, Sep. 2011, keynote talk.

[27] M. Bertozzi, L. Bombini, A. Broggi, M. Buzzoni, E. Cardarelli, S. Cattani, P. Cerri, A. Coati, S. Debattisti, A. Falzoni, R. I. Fedriga, M. Felisa, L. Gatti, A. Giacomazzo, P. Grisleri, M. C. Laghi, L. Mazzei, P. Medici, M. Panciroli, P. P. Porta, P. Zani, and P. Versari, "VIAC: An out of ordinary experiment," in *Proc. IEEE Intell. Veh. Symp.*, 2011, pp. 175–180.

[28] Volkswagen Group, *Driving Without a Driver—Volkswagen Presents the 'Temporary Auto Pilot'*, Wolfsburg, Germany, Press Release, Jun. 2011. [Online]. Available: http://www.haveit-eu.org/LH2Uploads/ItemsContent/117/HAVEit_Volkswagen_110621_PR_TAP_EN.pdf

[29] T. Gumpp, D. Nienhuser, R. Liebig, and J. M. Zöllner, "Recognition and tracking of temporary lanes in motorway construction sites," in *Proc. IEEE Intell. Veh. Symp.*, 2009, pp. 305–310.

[30] *CLAAS Steering Systems—Tracking Control Optimization*, 2011. [Online]. Available: http://www.claas.com/cc/servlet/contentblob/cl-pw/zzzz-Celum-DLC/pool/133959,bpSite=51524,property=data.pdf

[31] X. Zhang, M. Geimer, P. O. Noack, and L. Grandl, "Development of an intelligent master-slave system between agricultural vehicles," in *Proc. IEEE Intell. Veh. Symp.*, 2010, pp. 250–255.

[32] M. M. Moore and B. Lu, "Autonomous vehicles for personal transport: A technology assessment," *SSRN eLibrary*. [Online]. Available: http://ssrn.com/paper=1865047

[33] M. Campbell, M. Egerstedt, J. P. How, and R. M. Murray, "Autonomous driving in urban environments: Approaches, lessons and challenges," *Philosoph. Trans. Roy. Soc. A, Math. Phys. Eng. Sci.*, vol. 368, no. 1928, pp. 4649–4672, 2010.

[34] M. Aeberhard, S. Paul, N. Kaempchen, and T. Bertram, "Object existence probability fusion using Dempster-Shafer theory in a high-level sensor data fusion architecture," in *Proc. IEEE Intell. Veh. Symp.*, 2011, pp. 770–775.

[35] BMW Group, *Ready for Takeover!—Taking BMW Automated Vehicle Technology to the Motorway*, Munich, Germany, Press Release, Aug. 2011. [Online]. Available: https://www.press.bmwgroup.com/pressclub/p/pcgl/download.html?textId=144140&textAttachmentId=174417

[36] J. A. Bagnell, D. Bradley, D. Silver, B. Sofman, and A. Stentz, "Learning for autonomous navigation: Advances in machine learning for rough terrain mobility," *IEEE Robot. Autom. Mag.*, vol. 17, no. 2, pp. 74–84, Jun. 2010.

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